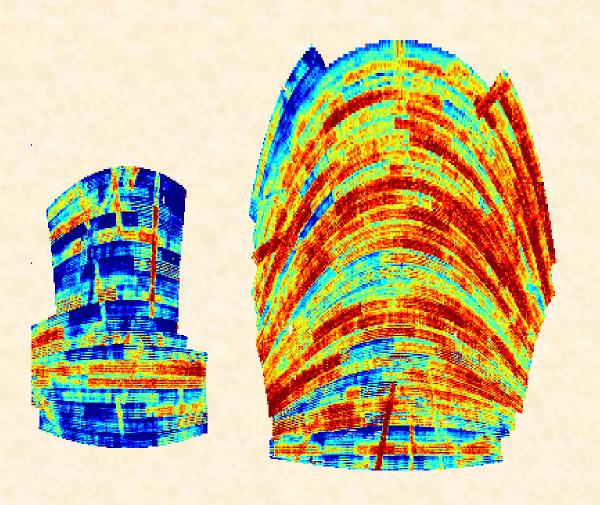
## Survey Depth and Randoms



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## Why Randoms?

#### Usual answer:

• It allows us to characterize the impact of a survey footprint on correlation functions.

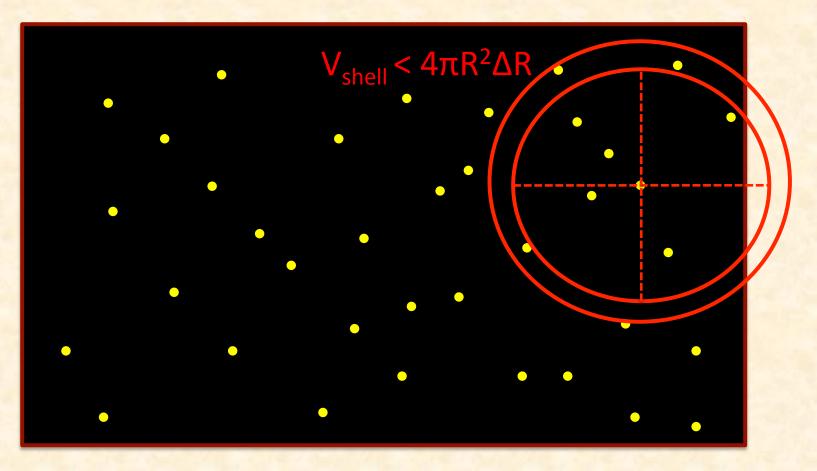
#### **BUT-**

This is only one of many possible selection effects.

We never observe the galaxy density field: we observe the density field modulated by the selection function.

### Effective Shell Volume

**DD** = number of data pairs in a shell of radius  $[R,R+\Delta R]$ 



Near the edges, not all parts of the shells are sampled.

### Why Randoms?

We can use **random catalogs** to characterize the impact of a selection function.

- Generate random catalog
- Apply selection criteria
- Resulting random point catalog will have structure introduced by selection.

## Creating Randoms

#### **Important:**

- Selection usually involves magnitude and color cuts!
- Random points should come tagged with magnitude and colors.
- Observational noise will introduce structure! E.g. Eddington bias.
- True magnitude and color of random galaxies needs to be scattered by observational noise.

How can we apply realistic noise?

#### The Problem

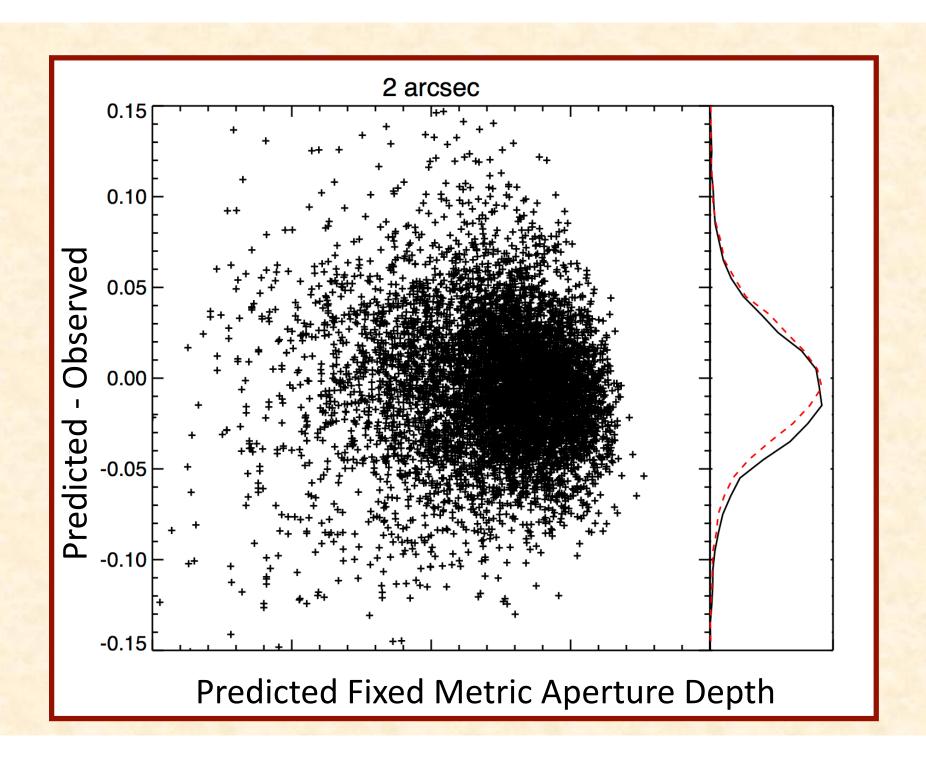
Surveys typically record the survey depth via some No limiting magnitude, e.g. fixed metric aperture, or PSF magnitude.

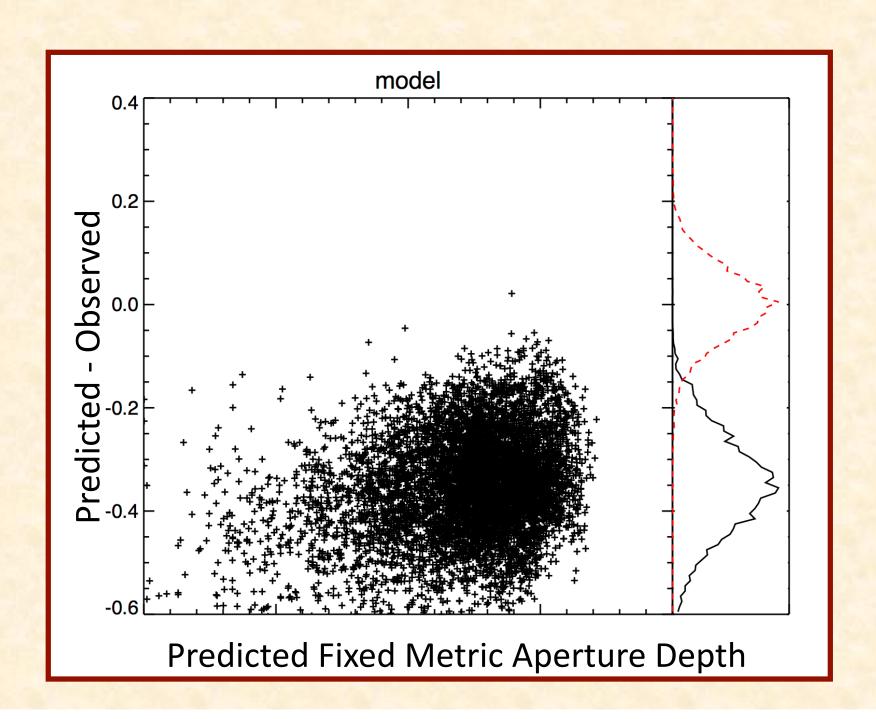
This is insufficient!

LSS science is not done with these apertures!

The recorded depth is related to the observed depth via systematics:

Observed Depth = F(recorded depth, PSF, dust, etc)





#### The Problem

Survey typically record the survey depth via some No limiting magnitude, usually a fixed metric aperture.

This is insufficient!

- Science is not done with fixed metric apertures.
- Generating noise for random points requires more than just the limiting magnitude!

How can we get at the noise of quantities we actually care about? (e.g. model magnitudes)

### A Solution

We can model the noise in the data:

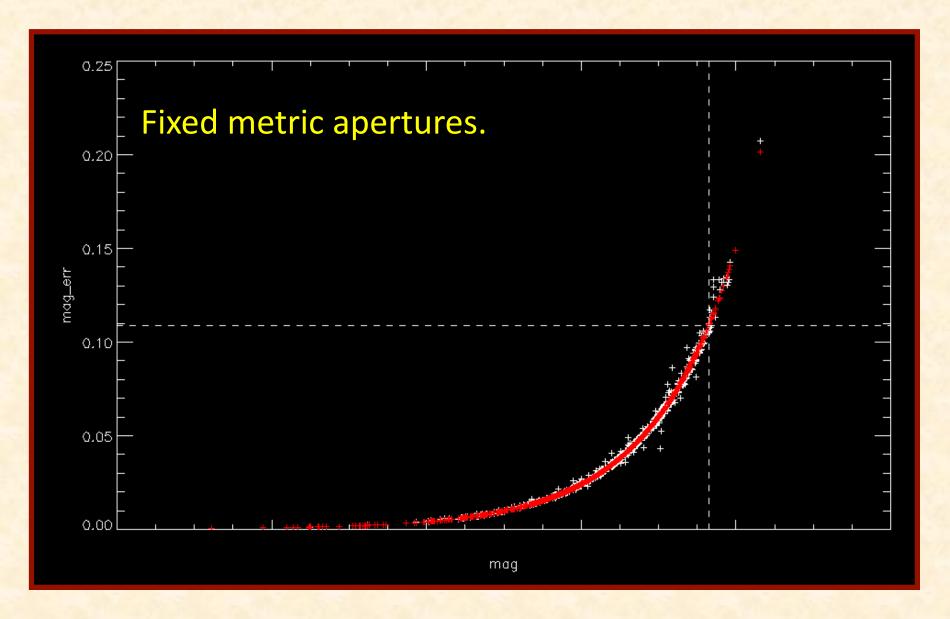
$$N_{photons} = (F_{sky,eff} + F_{source})xT_{exposure,eff}$$

$$\Delta N = N_{photons}^{1/2}$$

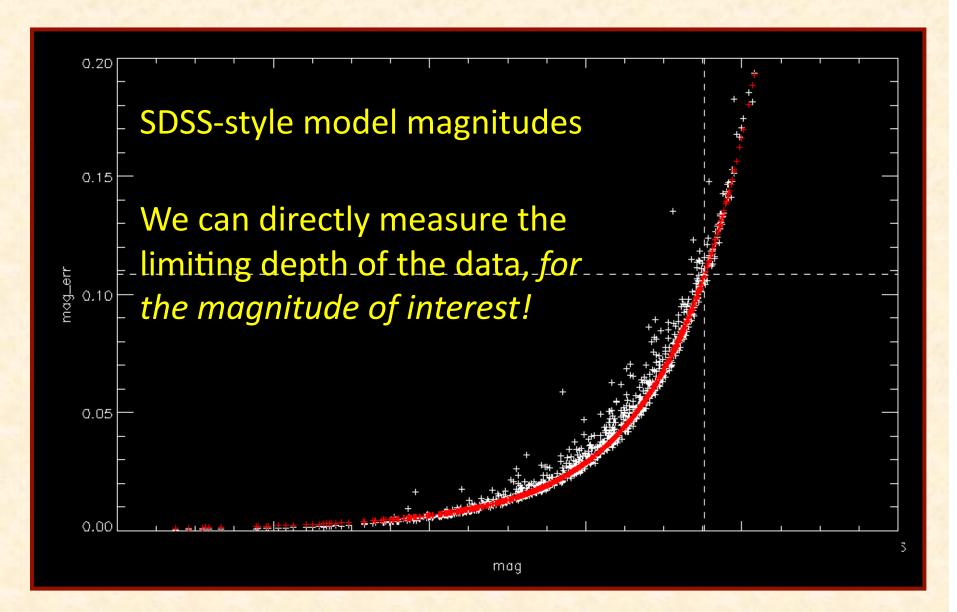
This is a model for magnitude error(obs. Magnitude)  $F_{sky,eff}$  can be recast in terms of the limiting mag.

We can fit this model to real data to estimate its limiting magnitude!

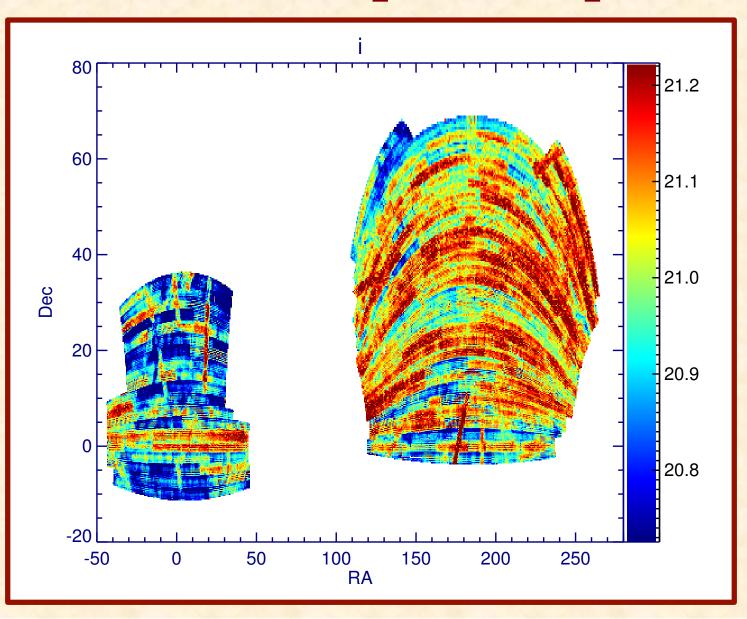
### DES Science Verification Data



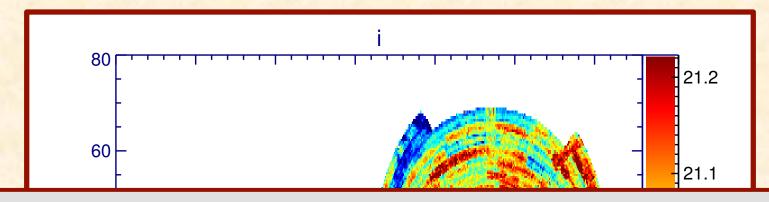
### DES Science Verification Data



# SDSS Depth Map

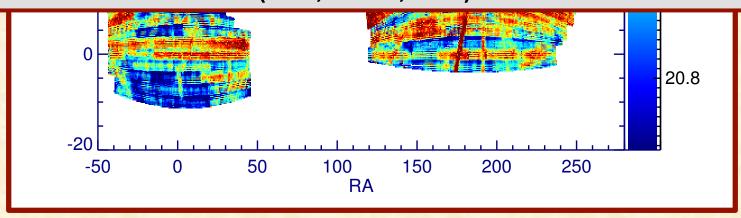


## SDSS Depth Map



Given exposure time and limiting magnitude, we make realistic noise realizations anywhere on the sky.

Noise automatically includes all relevant systematics! (PSF, dust, etc).



### The Problem

Fitting for the limiting magnitude requires sufficient galaxies in each pixel.

Resolution of empirical depth map is limited by the galaxy density.

In practice, LSST will have small scale depth variations (e.g. due to chip gaps).

This small scale structure is not captured with this approach.

### A Solution

Remember

Observed Depth = F(predicted depth, PSF, dust, etc)

Rather than work with the depth itself, we will work with the **fluctuation maps**.

Assume relation is linear!

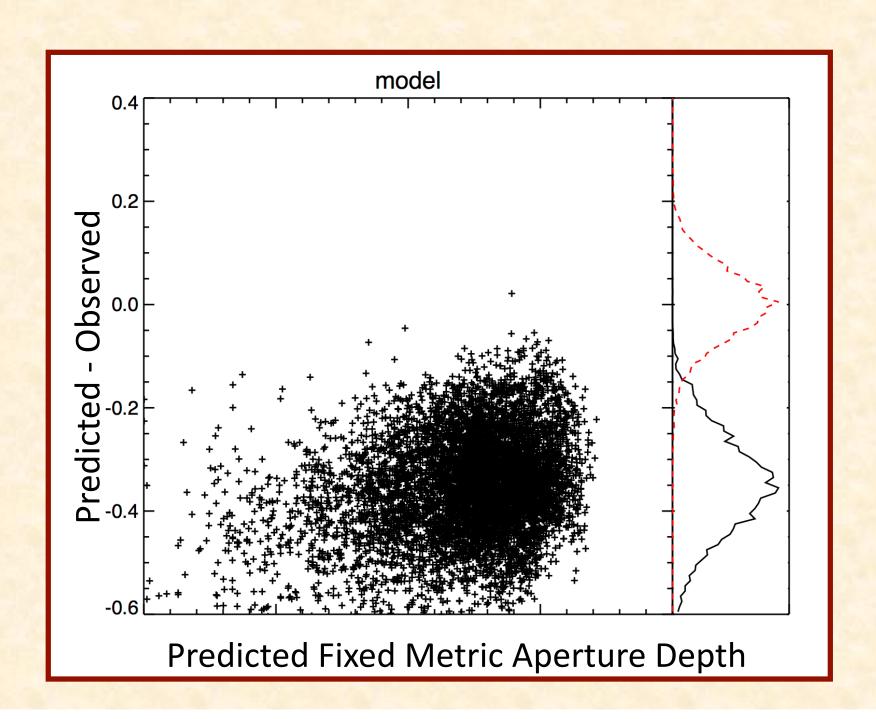
Obs. Depth =  $\sum a_i Map_i$ 

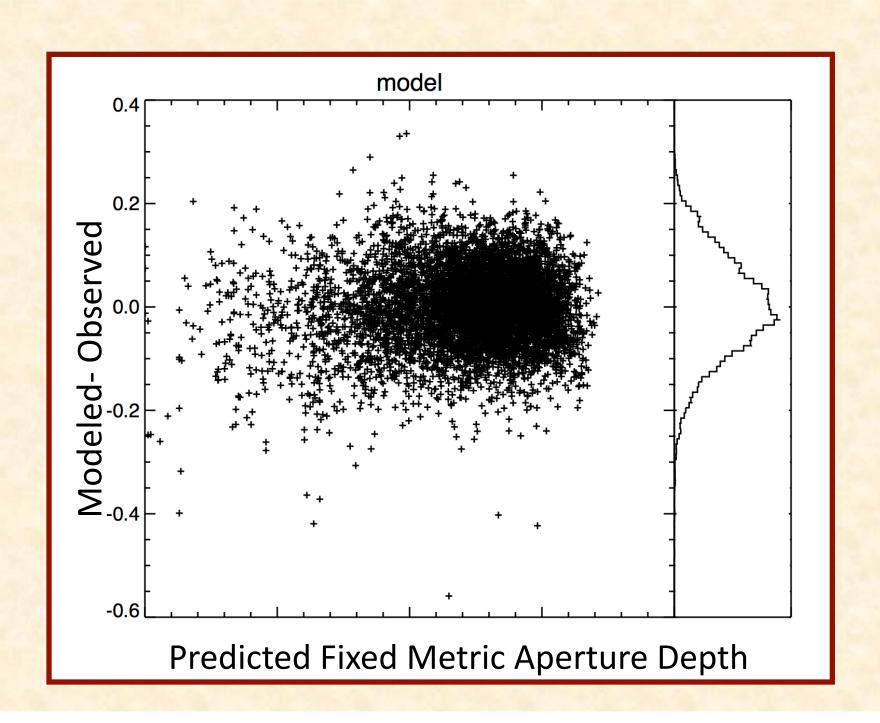
If we can measure the coefficients a<sub>i,</sub> we can predict the observed depth at the resolution of the maps Map<sub>i</sub>

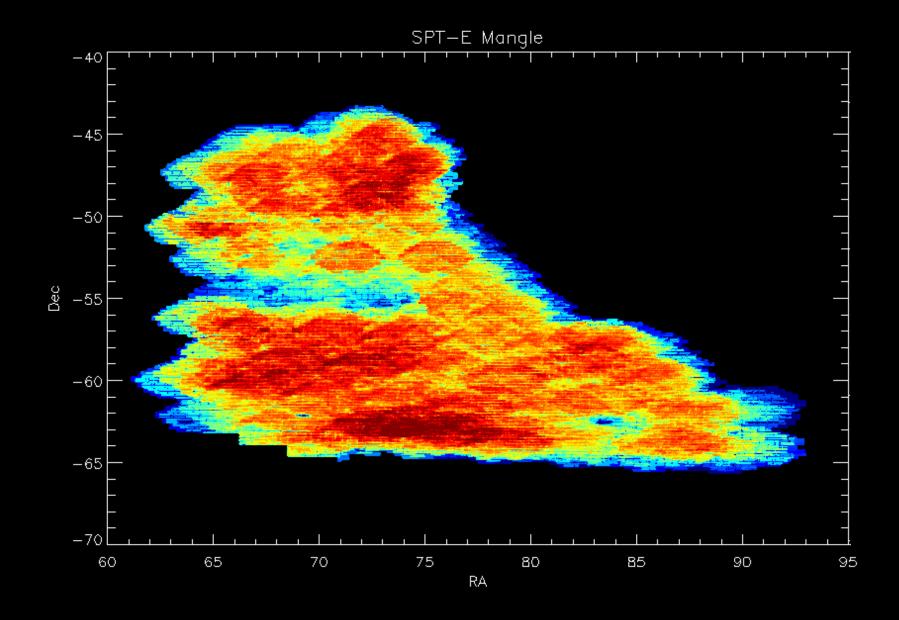
### A Solution

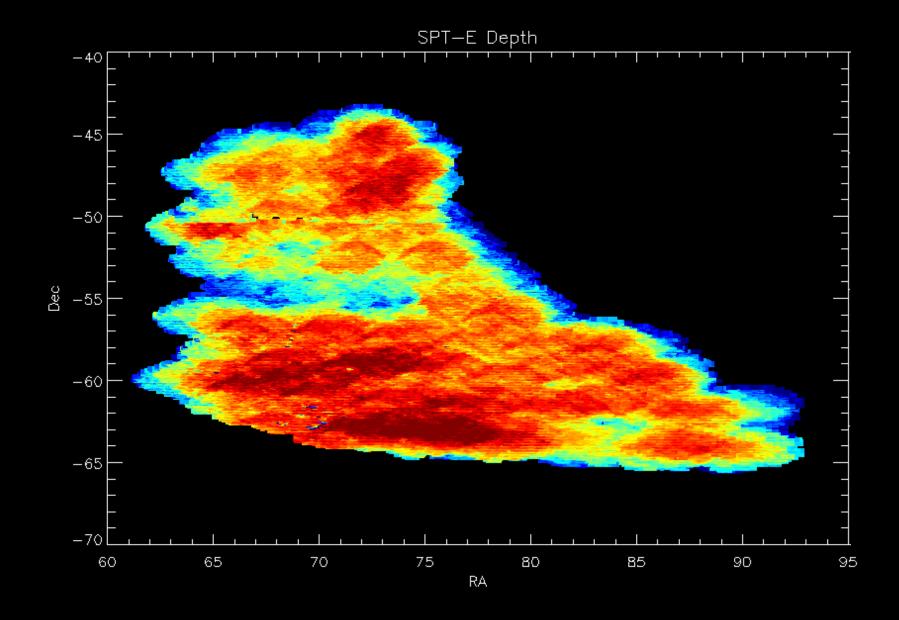
Solve for the coefficients using observed map!

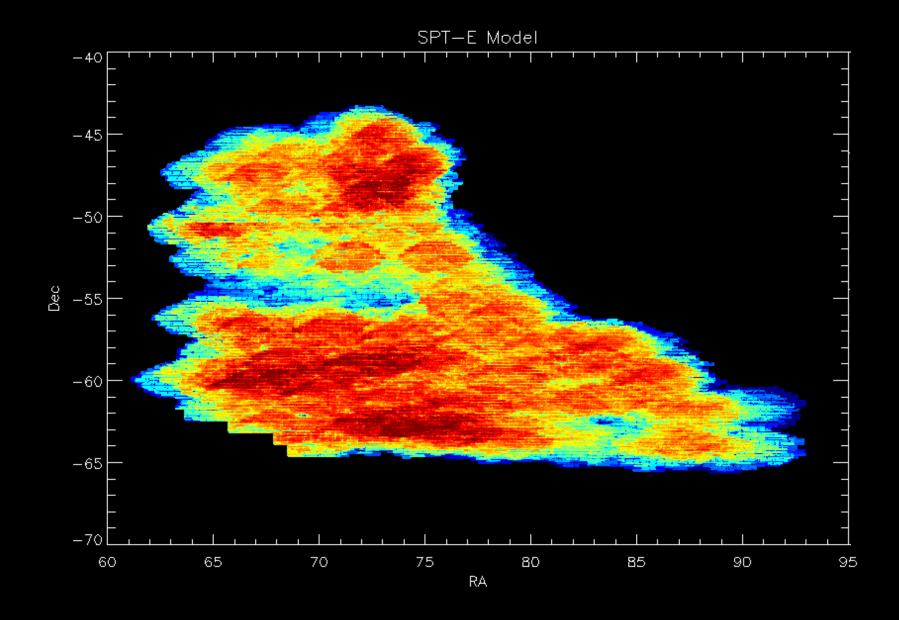
- De-res predicted map to resolution of observed depth map.
- Same for systematics maps.
- Fit for coefficients by minimizing rms of the residual map.
- Apply coefficients to high resolution map to get a high resolution model map of the "observed" depth.

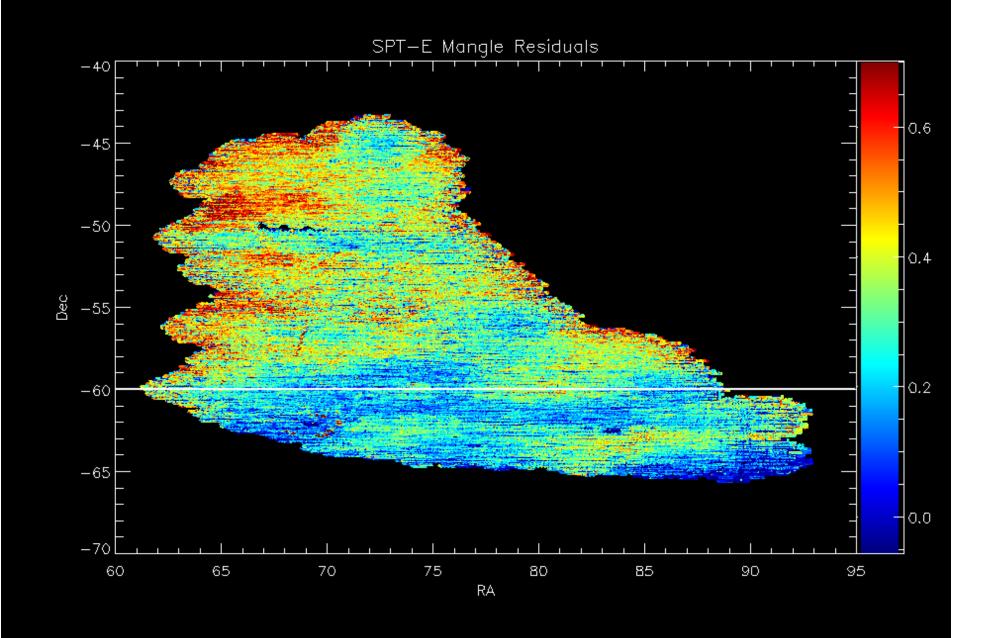


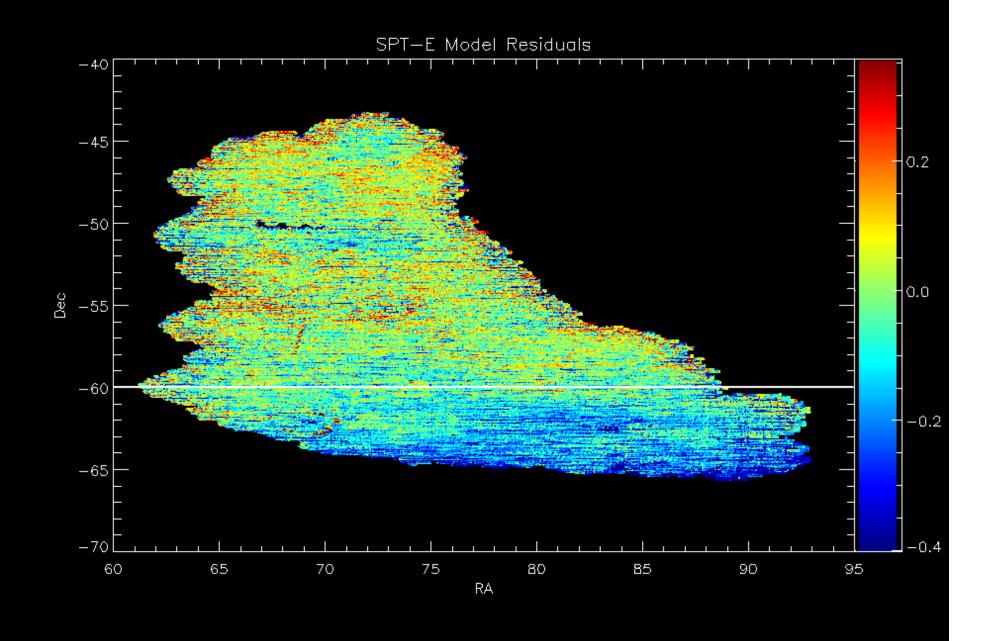












### **Bottom Line**

- Characterizing selection effects in LSS requires knowing the effective depth of the survey.
- •We can directly measure this for any magnitude definition of interest, and use it to generate randoms.
- The relation between the effective depth and the recorded depth depends on systematics (dust, psf).
- This relation is roughly linear in the residuals.
- Still to do: does machine learning methods improve upon the simple linear model?